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Understanding the relationship between marketing analytics, customer agility, and customer satisfaction: A longitudinal perspective.

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ABSTRACT

Shifting towards a more data-driven culture is a key antecedent of business success in today's digital era. Previous research has paid attention to exploring the influence of marketing analytics on business performance, and rarely examined how the use of marketing analytics influences customer agility and satisfaction. According to the dynamic capabilities view and using previous studies, we developed a conceptual framework to explore the effect of marketing analytics use on customer agility and customer satisfaction. In Study 1, we utilised cross-sectional data collected from 468 managers from various industries. In study 2, we employed longitudinal data in a three-wave longitudinal utilising a cross-lagged panel model. Study 1 indicated that data acquisition and tool acquisition are key drivers in adopting marketing analytics. Marketing analytics use has stronger effect on customer agility when market turbulence is high. They also revealed that the influence of customer agility on customer satisfaction in such conditions is stronger. Study 2 revealed that marketing analytics use at time point T1 has a significant and positive influence on customer agility at time point T2, while customer agility at time point T2 has a significant and positive influence on customer satisfaction at time point T3. These findings indicate strong temporal effects between marketing analytics use, customer agility, and customer satisfaction. The findings suggest that researchers should look beyond direct effects of marketing analytics use and shift their attention on how a marketing analytics can be leveraged to enable and support dynamic capabilities and customer satisfaction.

1. Introduction

To optimise an organisation's performance and make informed decisions, marketers use a technique called "marketing analytics," which entails gathering, maintaining, analysing, and applying marketing data (Agag et al., 2020; Liang et al., 2022a,b; Xu et al., 2016). Promotion, advertising, and the allocation of the marketing mix are all examples of crucial marketing functions that may benefit from the use of marketing analytics (Ahmed et al., 2022). "Marketing analytics [has not] lived up to its promise," despite the widespread recognition of the value of business analytics in strategic operational areas by both practitioners and academics (Hossain et al., 2022). More than half of senior managers are dissatisfied with the outcomes of their analytics, based on a survey conducted by Gartner in 2020. This has made them reluctant to use analytics for important decisions, despite their persistent expenditure on marketing data and related analytics (Agag et al., 2023a; Gartner, 2020).

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In addition, academics have urged deeper analysis of the link among marketing analytics and customers satisfaction (Agag, 2019; de Oliveira et al., 2023; Liang et al., 2022a,b).

The marketing capabilities of an organisation pertain to its capacity to effectively utilise its existing resources to carry out marketing activities and attain the required marketing outcomes (Bai et al., 2023). The marketing literature provides evidence suggesting that a company's marketing capabilities play a significant role in determining its marketing performance (Agag et al., 2020; Wegner et al., 2023). However, there is a scarcity of research that specifically investigates the mechanisms by which organisations enhance their marketing capabilities (Agag et al., 2023b; Cao and Tian, 2020). Simultaneously, scholarly investigations indicate that organisations can leverage marketing analytics to acquire valuable knowledge and insights from data, thereby enhancing their marketing capabilities and overall firm performance (Agag and Eid, 2020; Cao and Tian, 2020; Giacosa et al., 2022). However, there exists a dearth of theoretical and empirical comprehension regarding the specific mechanisms through which a company can effectively employ marketing analytics to enhance their marketing capabilities (Agag and El-Masry, 2016; Cao and Tian, 2020; Ritu et al., 2020). Moreover, scant attention has been given to the relationships between the use of marketing analytics, customer agility, and customer satisfaction (Cao and Tian, 2020; Vollrath and Villegas, 2022; Zhou et al., 2018). Hence, the main aim of this study is to address a fundamental research inquiry: "what are the mechanisms that enable a company to use marketing analytics to enhance customer agility thereby improving its customer satisfaction"?

In response to this call, the purpose of the present examination is to identify the circumstances in which marketing analytics might improve customer agility and satisfaction. We argue that marketing analytics improves customer satisfaction through customer agility (Akter et al., 2022). Customer agility denotes a company's ability to effectively detect and respond to consumers' demands (Aboul-Dahab et al., 2021; Giacosa et al., 2022; Hajli et al., 2020), and it serves as a leading indicator of a company's ability to analyse big data. Researchers in the fields of information systems (IS), marketing, and management have paid much attention to its potential as dynamic capabilities (Abdelmoety et al., 2022; Akter et al., 2021; Zhou et al., 2018). Analytics have been shown to improve agility in previous research (Tarn and Wang, 2023). Customers are more likely to be pleased with a company if it uses marketing analytics in its in-depth market research (Agag et al., 2019; Kalaignanam et al., 2021) and then prioritises projects to quickly identify and meet customer needs (Tseng et al., 2022). However, the mediating influence of consumer agility on the link among marketing analytics and consumers satisfaction link has yet to be empirically explored.

However, there are three main gaps in the current literature (Table 1). To begin with, the function of customer agility as a mediator among the use of marketing analytics and customer satisfaction has not yet been examined. Second, research on this topic has not considered the significance of a data-driven culture or the depth to which it has been

Table 2
Participant demographics.

Demographics	Study (1)/ Frequency	Study (2)/Frequency Percentage %		
	T (n = 468)	T1 (n = 308)	T2 (n = 264)	T3 (n = 239)
Gender				
Male	269	183	151	132
Female	199	125	113	107
Age				
<30	56	18	12	6
30–40	140	109	93	85
41–50	137	101	90	84
51–60	119	73	65	61
>61	16	7	4	3
Job Position				
Executive	35	5	3	1
Manager	409	291	259	237
Senior staff	23	12	2	1
Firm size				
<200 employees	42	11	8	6
200-500 employees	95	67	61	57
500-1000 employees	201	153	147	135
>1000 employees	130	77	48	41
Industry type				
Banking/finance	97	52	49	44
Computers/software	44	31	28	26
Consulting	37	22	17	15
Insurance	23	14	11	9
Manufacturing	19	8	7	5
Medicine/health	66	51	46	41
Publishing/ communications	78	60	53	52
Hotel/restaurants	29	11	9	7
Retail and wholesale trade	61	52	42	39
Others	14	7	2	1

Table 1
Recent studies on the analytics-agility relationships.

Studies	Relationships explored	Mediating effect	Data collection design	Key findings
Hajli et al. (2020)	The effects of big data analytics on customer agility and new product success	Not tested	Cross-sectional data	The use of data aggregation and analysis tools positively influences customer agility and new product success
Wamba et al. (2020)	The effect of big data analytics capability on supply chain agility and business	Not tested	Cross-sectional data	Big data analytics have positive effects on supply chain agility and business performance.
	The effect on knowledge management, exploration/exploitation, and strategic flexibility	Not tested	Cross-sectional data	Big data analytics capabilities significantly influence strategic flexibility via knowledge management and ambidexterity
Dubey et al. (2019)	The effect of big data analytics capability on supply chain agility and competitive advantage	Not tested	Cross-sectional data	Big data analytics capability positively influences supply chain agility and competitive advantage.
Ashrafi et al. (2019)	The business analytics capabilities-agility relationship	Not tested	Cross-sectional data	Business analytics positively affect information quality and innovative capability, and thereby firm's agility.
Ghasemaghaei et al. (2017)	The effect of using data analytics on agility	Not tested	Cross-sectional data	The use of data analytics is not significantly related to a firm's agility.
Corte-Real, Oliveira and Ruivo (2017)	The effect of knowledge assets created by big data analytics on agility and thereby competitive advantage	The mediating effect of agility on the knowledge -competitive advantage link	Cross-sectional data	Agility partially mediates the impact of the knowledge assets created from big data analytics on competitive advantage.
The current study	The effect of marketing analytics on customer satisfaction	Tested and supported	Longitudinal data	Customer agility mediates the impact of marketing analytics on customer satisfaction.

explored so far (Tseng et al., 2022). Finally, there is an obvious gap in our knowledge of the way in which data acquisition and tool acquisition impact the use of marketing analytics. Hence this area needs further research, especially in the context of the marketing analytics-driven workplace culture (see Table 2).

Moreover, few studies have examined the link among marketing analytics use, customer agility, and customer satisfaction. However, those studies utilised cross-sectional design to examine these relationships (e.g., Dash et al., 2021), demonstrating inconclusive findings. Multiple time periods have not been used to investigate this link. There has been widespread support for some time now for the use of longitudinal data in studies of marketing analytics use, agility, and customer satisfaction (see, for example, Wamba, 2022). It may be difficult to grasp the true value of marketing analytics and customer agility unless this link is evaluated over the course of several years. Our study's overarching objective is to address this research gap by exploring the moderating influence of a data-driven culture and market turbulence on the link among marketing analytics use, customer agility and customer satisfaction using a longitudinal data. Therefore, our research addresses the following research questions.

RQ1 "How can marketing analytics use and customer agility enhance customer agility over time"?
RQ2 "Does market turbulence moderate the relationship between marketing analytics use, customer agility, and customer agility over time"?
RQ3 "Does data-driven culture moderate the link between marketing analytics use, customer agility, and customer agility over time"?

Our paper makes theoretical contributions to the previous studies in several ways. First, it adds to the likelihood of marketing analytics use by exploring its drivers (i.e., data acquisition, tool acquisition). Second, our research responds to calls for more exploration of the relationships between marketing analytics and agility (Liang et al., 2022a,b; Mikalef et al., 2020). Third, it contributes to customer agility by investigating the mediating role of customer agility on the link among marketing analytics use and consumer satisfaction using longitudinal data. It indicates the benefits that follow when companies respond to consumers' needs and demands, which in turn improves customer satisfaction. Finally, our study demonstrates the benefits of a data-driven culture in the context of marketing analytics use and customer agility.

2. Literature review

2.1. Customer agility

Both practitioners and academics have paid attention to the issue of how businesses might adapt to uncertain and changing circumstances. Among these broad research perspectives, two competing schools of thought have developed. Examining how a company's structure and adaptability affect its capacity to respond to its environment is the focus of the static viewpoint (Zheng et al., 2022). In contrast, the dynamic view seeks to explain how businesses acquire, exploit, and reorganise adaptive capacities in response to shifting contexts (Chatfield and Reddick, 2018). In contrast to the concept that enterprises are passive and respond to changes in their environment, the dynamic view holds that they actively shape their industry's competitive landscape (Hadjielias et al., 2022; Stylos et al., 2021). In today's highly competitive business climate, agility has become a crucial factor for survival (Giacosa et al., 2022; McIver et al., 2018). As a result, we define marketing agility and its function in today's businesses through a forward-looking lens.

Customer agility refers to "firms' ability to leverage the voice of the customer for gaining market intelligence and detecting competitive action opportunities" (Zhou et al., 2018, p.516). In addition to consumer agility, Liu et al. (2016) offered partnering agility, which emphasises collaboration with vendors and distributors, and operational agility, which emphasises the smooth functioning of internal operations. Consumer agility, in contrast to the other two forms of agility, emphasises the value of firms' contacts with consumers and the role that customers play in driving firms' competitive activities in an uncertain market (Krotov et al., 2015). It is more challenging to acquire and maintain a competitive edge in today's economic climate due to the speed of globalisation, changing client needs, the intense competition, and innovative technical developments (Ghasemaghaei et al., 2017). Instead, success in today's hypercompetitive market requires what has been dubbed "customer agility": "the capacity to continually launch and leverage competitive activities to establish a succession of transient advantages" (Sultana et al., 2022). Firms which have achieved consumer agility are better equipped to tailor their offerings to individual consumers and improve their consumers' satisfaction (Zhou et al., 2018). In addition, businesses with increased customer agility may better respond to market possibilities since they are better able to incorporate consumers' creative ideas and feedback into the development of new products and services (Sultana et al., 2022; Tseng et al., 2022).

At its core, customer agility is about allocating resources to adapt to fluctuating market circumstances and establishing new routines to better meet the needs of an unpredictable future. Agility development sometimes relies heavily on information technology (IT) resources (Awan et al., 2022). Researchers have started to realize that needs are hidden in user-generated material, including social media posts, transaction data, and online reviews (Zhang et al., 2022). As a result, we find consumer adaptability a crucial result of investing in data-driven marketing analytics. In addition, we state that businesses with strong marketing agility may boost consumer happiness.

2.2. Marketing analytics

Analysing marketing data to draw conclusions and improve performance and decision making is the aim of marketing analytics, which falls under the broader umbrella of business analytics (Branda et al., 2018; Grover, 2022; Ruan and Mezei, 2022). Marketing analytics is "a domain of business analytics, and involves the collection, management, analysis, and usage of marketing data to obtain insights for decision making and performance optimization" (Wedel and Kannan, 2016; P.117). However, companies may differ in their implementation of marketing analytics and the analytical insights used in strategic decision making (Alsuwaidi et al., 2022; Ciampi et al., 2022; Mainardes et al., 2023). Nonetheless, marketing analytics are typically used in strategic marketing planning for purposes like market advertising, segmentation, marketing mix allocation, and developing new products (Alyahya et al., 2023a; Iacobucci et al., 2019; Zhou et al., 2018). As an example, consider how Amazon increased its sales of the smartphone game Air Patriots by conducting online experiments to see how consumers reacted to a new update to the game. Using marketing analytics, Amazon figured out how to tweak the game and raised its sales by 25% (Battleson et al., 2016).

Existing literature within the field of business analytics investigates the efficacy of analytical endeavours, particularly big data analytics. Pereira et al. (2019), using a resource-based perspective, argue that businesses may optimise their performance by analysing their data. Insights like this help businesses create goods and services that are more in tune with what their customers want and need, which in turn improves business performance. Moreover, organisations may have access to timely data using business analytics that contributes to strategic decision making, leading to sustainable competitive advantages and enhanced company performance (Alyahya et al., 2023b;Yokoyama et al., 2022; Zhou et al., 2019). Business analytics have been shown to improve many different aspects of a firm's performance, including its financial performance (Hsu and Lin, 2023; Yang et al., 2020), its market performance (Liang et al., 2022a,b), its competitive advantages (Hossain et al., 2022), and its innovation performance (Ghasemaghaei and Calic, 2020). We argue that data driven marketing analytics is a key driver of customer agility.

2.3. Dynamic capabilities theory

The notion of dynamic capabilities is frequently employed in the analysis of variations in business performance. According to this theory, certain firms outperform others due to their superior ability to sense, seize, and reconfigure capacities in response to a dynamic and evolving environment (Teece, 2007, 2015). The dynamic capabilities theory, as evidenced by its application in the marketing and IS context (Mikalef et al., 2021; Saenz et al., 2022), provides a theoretical framework for comprehending how organisations can develop dynamic capabilities and enhance their business performance through marketing endeavours. For example, previous research has indicated that the implementation of knowledge generation procedures, such as marketing controls (Liang and Frosen, 2020) and marketing analytics (Liang et al., 2022a,b), plays a significant role in fostering the advancement of dynamic capacities. This study considers dynamic capabilities view to be an extension of the resource-based view. Both theories have been extensively employed to elucidate the variations in company performance. However, dynamic capabilities theory lays particular emphasis on the influence of organisational and environmental factors on firm performance. Hence, we posit that it presents a valuable theoretical framework for comprehending the impact of marketing analytics on customer satisfaction via the lens of customer agility.

3. Conceptual framework and hypotheses development

We used dynamic capabilities theory to develop our conceptual framework. From the dynamic capabilities' perspective, some organisations outperform others because they are better at detecting, seizing, and reconfiguring capability to meet the changing environment (Blome et al., 2013). "Dynamic capabilities theory" provides a theoretical basis for our study to work out how organisations may foster dynamic capabilities and increase company performance through marketing initiatives (Jafari-Sadeghi et al., 2022; Gyemang and Emeagwali, 2020; Tueanrat et al., 2021).

According to the illustration provided in Fig. 1, it is posited that the utilisation of marketing analytics by a company can contribute to the creation of knowledge assets that play a crucial role in its dynamic capabilities, specifically in terms of customer agility. Furthermore, the idea of dynamic capacities emphasises the combined influence of resources and contingency variables on performance outcomes. It underscores the importance of aligning organisational practises with the evolving environment (Teece, 2014). Therefore, it is posited that the impact of marketing analytics on customer satisfaction can be influenced by a combination of organisational practises, including the cultivation of a data-driven culture, and external factors such as market turbulence.

3.1. Data acquisition and marketing analytics

Data plays a crucial role in an organisation (Chaudhuri et al., 2021a,b), and it can be obtained from several functional domains such as human resources, operations, marketing, finance, and other relevant areas (Zahoor et al., 2022). In order to facilitate more successful innovation in an organisation, it is imperative that the data obtained possesses certain characteristics. Specifically, the data should be deemed valuable, inimitable, scarce, and non-substitutable (Harvey and Turnbull, 2020; Irfan et al., 2019). These attributes align with the core tenets of the Resource-Based View (RBV) philosophy (Barney, 1991). Ensuring data quality is a crucial aspect in facilitating the ease and effectiveness of data analysis within the realm of technology (Akter et al., 2022; Gunasekaran et al., 2017). The leadership of an organisation in a specific functional domain can have a significant impact on the acquisition of carefully selected, valuable, unique, and non-replaceable data (Agag et al., 2024; Ashrafi et al., 2019; Chaudhuri et al., 2021a,b). The utilisation of traditionally obtained data, also known as legacy system data, holds significant importance within the realm of marketing analytics (Liang et al., 2022a,b). Marketing analytics can be utilised by organisations to effectively examine real-time data (Alghamdi and Agag, 2023b; Chaudhuri et al., 2021a,b; Hajli et al., 2020). Various types of data, such as internal and external data, including big data, have been identified in the literature (Gnizy, 2019; Kalaignanam et al., 2021). The acquisition of relevant data is crucial for organisations seeking to implement marketing analytics strategies. Therefore, the following hypothesis is formulated.

H1. "Data acquisition has a positive influence on marketing analytics use".

3.2. Tool acquisition

The accurate analysis of obtained data is facilitated through the utilisation of marketing analytic tools (Liang et al., 2022a,b). The selection of a marketing analytics tool for an organisation is contingent upon the inherent characteristics of the data (Alghamdi and Agag, 2023a; Hossain et al., 2022; Tarn and Wang, 2023). The decision about the utilisation of either an on-premises tool or a cloud-oriented solution is made by the organisation (Chaudhuri et al., 2021a,b). The consideration of user experience also plays a crucial role in the decision-making process of organisations when selecting appropriate tools (Alyahya et al., 2023c; Kalaignanam et al., 2021; Morimura and Sakagawa, 2023). In order to facilitate the successful implementation of a marketing analytics solution inside an organisation, it is imperative to provide users with appropriate training (Alzaidi and Agag, 2022: Ashrafi et al., 2019; Shamout, 2023). Therefore, it is imperative for organisations to procure

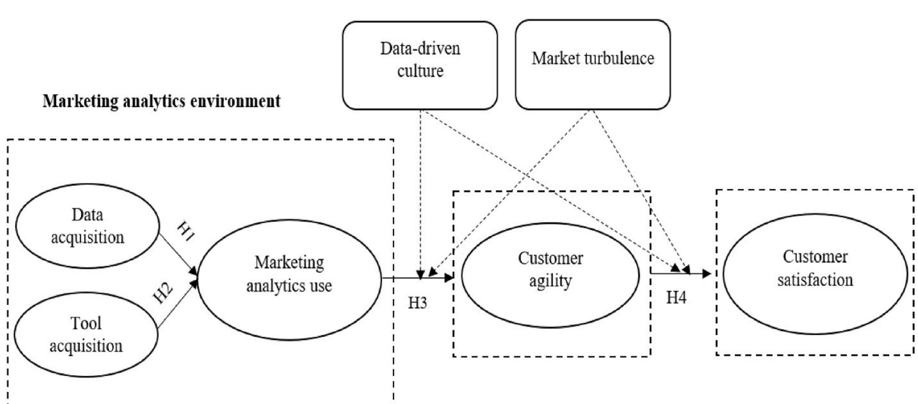

Fig. 1. Research model.

the appropriate instrument when implementing a marketing analytics system. Based on the preceding discourse, it is apparent that the tool acquisition plays a crucial role in marketing analytics, exerting an influence on business performance by enhancing agility and facilitating real-time decision-making (Alyahya et al., 2022; Chatterjee et al., 2021). According to Roy et al. (2017), customer satisfaction is ultimately influenced by agility. The RBV framework has effectively elucidated the relationship between the acquisition of marketing analytics capabilities and customer satisfaction, specifically through the two key components of data acquisition and tool acquisition. Therefore, we suggest the following hypothesis.

H2. "Tool acquisition has a positive influence on marketing analytics use".

3.3. The link between marketing analytics use and customer agility

According to Chaudhuri et al. (2021a,b), a data-driven culture sparked by marketing analytics helps businesses react quickly to opportunities and challenges in the market. Similarly, Liang et al. (2022a, b) discovered that marketing analytics affords businesses the chance to swiftly engage in consumer, internal, and external-process-sensing initiatives, enabling them to reallocate resources and re-configure processes in real time in response to shifts in the market. When a company is agile in the eyes of its customers, it can adapt quickly to new trends and tastes (Hajli et al., 2020). As a result, businesses have a greater chance of achieving such performance goals as increased revenue, decreased expenses, and expanded market share (Ashrafi et al., 2019).

Furthermore, according to the research conducted by Duan et al. (2020), it is indicated that the implementation of business analytics has the potential to foster a culture that relies on data-driven decision-making. This, in turn, enables organisations to effectively and promptly recognise both market possibilities and potential threats, and subsequently take appropriate actions in response. In a similar vein, Liang et al. (2022a,b) have discovered that marketing analytics offer prospects for organisations to promptly participate in customer-centric, internal process-oriented, and external process-oriented sensing endeavours. These activities enable firms to effectively redistribute resources and adapt real-time processes in response to market fluctuations (Mikalef et al., 2021). The ability of a corporation to adapt to changing customer needs and market conditions, known as customer agility, enables it to enhance its innovation capabilities and proactively seize emerging market possibilities (Liang et al., 2022a,b). Therefore, it is most probable that they will encounter enhanced performance, including increased profitability, decreased expenses, and enhanced client satisfaction (Ashrafi et al., 2019). This elicits the following hypotheses.

H3. "Marketing analytics use has a positive influence on customer agility".

3.4. Customer agility and customer satisfaction

The term "customer satisfaction" refers to a good emotional state that results from a favourable evaluation of the consumer's experiences with a company (Zhou et al., 2018). Many important performance consequences have been connected to consumers' satisfaction as a significant motivator of behavioural intentions (Chaudhuri et al., 2021a,b). Thus, there has been much research on consumer satisfaction in the fields of marketing, with findings suggesting that providing timely replies to consumers' requests boosts satisfaction (McIver et al., 2018). Rahman et al. (2021) discovered that consumers are happier when supply and demand are dynamically aligned. Likewise, pleased consumers are those who have a sense of being heard and understood (Škare and Soriano, 2021; Zheng et al., 2022). Our contentment is reinforced by the prospect of timely delivery (Rahman et al., 2021). Since customer agility involves quickly responding to consumers' requests, it stands to reason that companies that put an emphasis on customer agility tend to have more satisfied customers who return for more purchases. Zhou et al. (2018) revealed that customer agility is a key driver of customer satisfaction. Therefore, we suggest the following hypothesis.

H4. "Customer agility has a positive influence on customer satisfaction".

3.5. The moderating role of market turbulence

Market turbulence is a major type of environmental change (Zhou et al., 2019). Company processes and technology are jeopardised by the fact that market turbulence may cause sudden and severe changes in consumer wants and preferences (Elazhary et al., 2022). At times of market upheaval, companies face disruption to their business models and must quickly adapt by revising even their most fundamental procedures (Sheng et al., 2021). To keep their edge in the market, they may need to increase their IT spending to boost operational efficiency. Moreover, organisations benefit from a more effective use of such resources as IT, via sharing and greater coordination across various business divisions (Sheng et al., 2021).

Market turbulence impairs the effectiveness of decision-making processes because it compels new resources and skills to be allocated (Saha et al., 2017). Possible solutions include increasing spending on information technology to boost operational efficiency (Li et al., 2021). A corporation under such duress would have to depend on a specialist department like IT, which manages the resources and skills that underpin mission-critical business activities. According to the literature, the value of dynamic capabilities increases in chaotic contexts since they make contributions to the organisations that enable it to cope with change (Akter et al., 2022). Agility is the ability to respond quickly to new circumstances and take use of them to your advantage. Yet the literature also displays inconsistencies. In very volatile circumstances when foreseeing future changes is difficult, it has investigated how dynamic capacities might become experiential and weakly connected with performance (McCann et al., 2009). Our research backs up the theory that customer-centric businesses are better equipped to quickly absorb and implement new knowledge. This ultimately results in high levels of customer satisfaction. Prior studies have pointed out that the effect of IT capabilities on agility and performance is stronger in high market turbulence (Elazhary et al., 2022). Thus, we suggested the following hypothesis.

H5. "Market turbulence moderates the relationships between the use of marketing analytics, customer agility, and customer satisfaction".

3.6. The moderating role of data-driven culture

The idea of a marketing culture that is heavily influenced by data analytics is not new (Chaudhuri et al., 2021a,b). The use of marketing analytics has captured the attention of academics (Bourguignon et al., 2021). To get the most out of a marketing analytics system and increase ROI, experts indicate that a company's culture must be conducive to using marketing analytics. According to Tseng et al. (2022), there is a link between data analysis and a company's culture. Chaudhuri et al. (2021, p. 19) define a data-driven culture as "a pattern of behaviours and practices by a group of people who share a belief that having, understanding and using certain kinds of data and information plays a crucial role in the success of their organisation". According to Tarn and Wang (2023), an organisation must adopt a new analytics-driven culture to improve its performance. A firm's performance may be influenced by a data-driven culture (Li et al., 2022). Prior studies reveal that a company's culture affects its information processing, rationality, and use of discretion in decision making (Rahman et al., 2021). Thus, the advantages of marketing analytics may be influenced by factors of the company's culture. Hence, we argue that data-driven culture is complementary to marketing analytics, which makes marketing analytics use more valuable when it comes to customer agility and customer satisfaction. Therefore, we suggest a final hypothesis.

H6. "A data-driven culture moderates the relationships between the use of marketing analytics, customer agility, and customer satisfaction".

4. Study 1: methodology

4.1. Sample and data collection

This study employed a professional market research firm to gather the required data for the purposes of the analysis. We conducted an online survey using Qualtrics and recruited eligible UK residents through Amazon's Mechanic Turk (MTurk). Previous studies have found that MTurk's data quality is superior to that of two expert panels (Qualtrics and Lightspeed) on a wide range of metrics (Kees and colleagues, 2017). The target respondents pool was obtained via utilising the Amazon Mechanical Turk service platform (www.mturk.com). Previous study has demonstrated that Mturk exhibits a substantial degree of test-retest reliability in the domains of marketing, management, and operations management. Consequently, it has emerged as a widely utilised instrument for data collecting in the field of marketing research (Ta et al., 2018). Prominent scholarly publications, like Industrial Marketing Management (Oakley et al., 2021) and Journal of Supply Chain Management (Pulles and Loohuis, 2020), have employed the utilisation of Amazon Mechanical Turk (Mturk) as a means of gathering data. It is important to note that there exist methods to improve the quality of data when gathering responses with Mturk. According to existing literature, the recruiting strategy and its subsequent implementation play a crucial role in ensuring the quality and reliability of data (Azadegan et al., 2022; Brazhkin, 2020). To ensure data quality we carefully screened the responses to remove any ineligible participants. We also followed the recent guidelines of Arndt et al. (2022) and used both statistical and direct screeners to enhance data quality. For instance, we asked participants several open-ended questions (e.g., "where are you from, what do you do") and if they provided nonsensical or improper answers, they were removed from the subject pool and replaced with quality responses.

Data were gathered from managers with at least two years of experience working in analytics-driven organisations in a variety of UK industries (namely, "retail," "consulting," "computers/software," "hotels," "manufacturing" "medicine/health," "banking and finance," and "the paper industry". A survey was pre-tested on 30 academics before the official data gathering procedure began. Executives and managers received invitations to take part in the survey itself from January to February 2021. Utilising the software G*Power 3.1 (Faul et al., 2009), we calculated a minimum sample size of 120 to gain the power of 0.8 in the Chi-square goodness of fit test, hence our sample was ample. Our study randomly collected 486 out of 700 participants, a response rate of 69%. Eighteen questionnaires were deemed invalid because of issues including missing data, liners issues, inconsistencies, or bias in the responses. This process yielded 468 completed and valid questionnaires for final analysis.

The responses received came from companies of a diverse industry background (e.g., "banking/finance, computers/software, consulting, insurance, manufacturing, medicine/health, publishing/communications, hotel/restaurants, retail and wholesale trade"). The largest proportion came from the banking and financial services sector (20.7%), followed by publishing/communications (16.6%), medicine/health (14.10%), and retail and wholesale trade (13.30%), while a large proportion came from a variety of other sectors (35.58%). The vast majority were large firms, accounting for 71.2% of the sample. The survey was predominantly targeted to senior managers, as they likely to be the most knowledgeable about strategic issues relating to marketing analytics and customer agility in the firm.

4.2. Measures

Our study used valid and reliable scales to assess all our study variables (see Appendix A). More precisely, customer satisfaction was evaluated utilising four items from prior studies (e.g., Mithas et al., 2011; Raguseo and Vitari, 2018) (e.g., "Improving the delivery of what our customers want"). Customer agility was operationalised using nine items adopted from prior research (e.g., Narver et al., 2004; Shirazi et al., 2022; Slater and Narver, 2000) (e.g., "We continuously try to discover additional needs of our customers of which they are unaware"). The use of marketing analytics was assessed using five items from Akter et al. (2019) and Sharda et al. (2016) (e.g., "I believe that marketing analytics solution can help the organisation for taking accurate decision at appropriate time"). We used four items from previous research to assess data acquisition (e.g., Cosic et al., 2015; Gnizy, 2019; Gunasekaran et al., 2017; Sharma et al., 2014) (e.g., "I understand the importance of acquiring appropriate data for marketing analytics solution"). Tool acquisition was measured using three items from Bayrak (2015) and Sun et al. (2017) (e.g., "appropriate tool acquisition is essential for effective marketing analytics solution"). Market turbulence was assessed using four items from previous research (Elazhary et al., 2022; Jaworski and Kohli, 1993) (e.g., "In our kind of business, customers' product preferences change quite a bit over time"). Finally, the data-driven culture was measured using three items from Yu et al. (2021) (e.g., "We continuously assess and improve the business rules in response to insights extracted from data"). All measures were assessed using a 5-point Likert scale.

Based on a set of independent-samples t-tests, the analysis revealed that there was no statistically significant distinction ($p > 0.05$) observed among the three groups of participants in relation to the average values of the primary constructs and the moderating variables included in the model. The factor analysis conducted on multiitem constructs demonstrated a high level of consistency in the factor loadings, suggesting that the measurement invariance was maintained across all three groups of respondents. A set of independent-samples t-tests was conducted to examine the presence of nonresponse bias within three distinct groups of respondents: individuals who dropped out after T1, those who dropped out after T2, and individuals who did not drop out. The findings revealed that there was no statistically significant distinction ($p > 0.05$) in relation to the participants' demographic characteristics. Therefore, the act of dropping out was perceived as being haphazard rather than following a structured pattern, and the potential influence of nonresponse bias was not a major concern.

4.3. Common method bias

When respondents cannot deliver correct replies and/or when they are reluctant to try to provide accurate responses, a typical technique bias is likely to arise in marketing research (Podsakoff et al., 2012, p.534). Many measures were taken in the design and analysis of the present examination to reduce the impact of common method bias. First, we performed a Harman one-factor test to investigate the potential impact of common method bias. According to our findings, the covariance could not be attributed to a single factor. Second, in order to get reliable results from this survey, we specifically targeted individuals with the necessary expertise and understanding of the issue (i.e., "executives and/or managers"). Third, a marker variable method was employed to assess for common method bias. Our analysis demonstrated no significant variances to the links among the study variables and the partialled correlations were reduced ($r = 0.03$) (Podsakoff et al., 2012). Additionally, the model specification employed in our study was intricate, leading us to doubt that the participants could have anticipated the outcomes. Furthermore, we took measures to guarantee the privacy and confidentiality of the data gathered, and we explicitly stated this to the participants, emphasising the importance of providing truthful responses to the survey questions. Additionally, we conducted an analysis of variance inflation factors and determined that the presence of multicollinearity is unlikely to impact our interpretation of the findings, as indicated by a maximum VIF of 1.308, which is considered very low.

Furthermore, in order to assess the presence of nonresponse bias within our sample, we conducted a comparative analysis between the characteristics of the respondents and those of the individuals listed in the mailing database for each organisation. These characteristics included factors such as company size and industry of operation. The chi-square analysis indicated the absence of any discernible patterns of response bias. In addition to nonresponse, we also investigate the presence of late-response bias by conducting chi-square tests on early (first two weeks) and late replies (last two weeks) with regard to business size, industry, expenditure, and firm experience with marketing analytics. The results indicated that there were no statistically significant differences.

5. Study 1: results

We decided to use Smart PLS-SEM (Hair et al., 2021) to estimate our theoretical framework because of its adaptable distributional assumptions and strong predictive robustness. There were two stages of evaluation for the conceptual framework. The structural model was evaluated after the measurement model was evaluated (Hair et al., 2021).

5.1. Measurement model

"Confirmatory factor analysis" (CFA) was performed using SmartPLS 3 on all of the model's constructs to ensure the model's validity and reliability (see Table 3). Good internal reliability was indicated by Cronbach's alphas and composite reliability (CR) ratings that were all higher than the cut-off value of 0.70. Convergent validity was established when all the items were loaded onto their predicted variable (factor loadings >0.70) with average variances extracted (AVE) > 0.50. The square root of the AVEs was greater than the correlation between the different variables, demonstrating their discriminant validity (see Table 4). For each key factor, we also calculated the corresponding "heterotrait-monotrait" (HTMT) ratio, according to Hair et al. (2021). "Discriminant validity" was further supported by the finding that all the HTMT values (between 0.03 and 0.59) were less than the cut-off value of 0.85 and that the "95% confidence intervals" did not include 1.

Table 4
Discriminant validity.

Variables	SAT	AGT	ANL	DAQ	TAQ	MAT	MNC
SAT	**0.778**[a]						
AGT	0.419	**0.833**					
ANL	0.328	0.590	**0.767**				
DAQ	0.390	0.318	0.417	**0.769**			
TAQ	0.254	0.489	0.388	0.470	**0.835**		
MAT	0.408	0.332	0.470	0.336	0.319	**0.780**	
MNC	0.335	0.286	0.331	0.490	0.467	0.510	**0.712**

[a]The diagonal is the square root of the AVE of the latent variables and indicates the highest in any column or row.

Table 3
Measurement statistics of construct scale.

Construct/Indicators	Standard Loading	CR	VIF	Cronbach's α	AVE	Mean	SD	t-statistic	Skewness	Kurtosis
Customer satisfaction (SAT)										
SAT1	0.93	0.96	1.245	0.93	0.606	3.02	0.89	19.29	−1.12	2.20
SAT2	0.96					2.28	0.85	24.30	−1.57	3.08
SAT3	0.94					3.08	0.87	22.95	−0.88	2.567
SAT4	0.92					2.80	0.82	27.34	−1.47	2.120
Customer agility (AGT)										
AGT1	0.94	0.94	1.673	0.92	0.694	2.73	0.93	11.29	−1.67	2.04
AGT2	0.90					2.94	0.85	32.09	−1.29	2.13
AGT3	0.93					3.08	0.89	22.98	−1.89	2.07
AGT4	0.89					2.85	0.78	23.20	−1.73	1.89
AGT5	0.90					2.37	0.84	18.45	−1.25	2.03
AGT6	0.94					2.89	0.90	23.90	−1.44	2.36
AGT7	0.96					2.03	0.87	16.40	−1.04	2.67
AGT8	0.93					3.19	0.84	26.41	−1.26	2.12
AGT9	0.96					3.07	0.81	27.45	−1.74	2.87
Marketing analytics adoption (ANL)										
ANL1	0.94	0.95	1.754	0.93	0.588	2.89	0.83	20.12	−2.30	1.03
ANL2	0.95					3.02	0.89	29.45	−1.89	2.24
ANL3	0.90					2.99	0.87	18.37	−2.04	1.78
ANL4	0.96					3.01	0.80	20.38	−1.64	2.40
ANL5	0.90					2.37	0.89	14.08	−1.37	2.19
Data acquisition (DAQ)										
DAQ1	0.94	0.95	1.732	0.93	0.590	3.03	0.86	21.20	−2.40	2.49
DAQ2	0.92					2.78	0.84	25.38	−1.25	1.62
DAQ3	0.90					3.06	0.89	12.36	−1.84	1.57
DAQ4	0.95					2.49	0.88	21.89	−2.06	2.09
Tool acquisition (TAQ)										
TAQ1	0.95	0.93	2.091	0.91	0.697	3.04	0.85	24.30	−2.30	1.56
TAQ2	0.93					2.57	0.89	21.29	−2.56	2.34
TAQ3	0.90					2.90	0.86	37.20	−1.90	1.09
Market turbulence (MAT)										
MAT1	0.94	0.95	1.89	0.93	0.609	2.56	0.88	20.25	−1.54	1.30
MAT2	0.90					3.04	0.85	16.49	−1.30	1.56
MAT3	0.96					3.30	0.80	24.30	−1.23	1.89
MAT4	0.91					3.18	0.88	19.12	−1.29	2.90
Marketing analytics-driven culture (ANC)										
MNC1	0.95	0.97	1.129	0.95	0.508	3.34	0.86	34.20	−2.04	1.30
MNC2	0.97					2.89	0.88	28.12	−1.78	1.26
MNC3	0.91					2.45	0.89	21.47	−1.45	1.53

5.2. Structural model

There is no assumption of normality in PLS. As a result, we have not relied on the more common parametric methods for conducting statistical tests of significance. Standard errors (SEs) and significance levels (SEs) for parameter estimations are estimated via a bootstrapping technique in PLS (Peng and Lai, 2012). Our results offered evidence of our measurement model's validity and reliability. Thus, we investigated the structural model to test the proposed hypotheses. We followed the recommendations by Hair et al. (2021) to test the study hypotheses. Our study explains 42% of variance for adopting marketing analytics, 37% of variance for customer agility, and 51% for customer satisfaction.

To test the study hypotheses (H1-H5), the structural model was tested by examining the associations among the study variables (see Fig. 2). Our analysis indicated global fit indicators, APC = (0.176, $p < 0.001$), ARS = (0.834, $p < 0.001$), AARS = (0.788, $p < 0.001$), AVIF = (2.189), and GOF = (0.841). Our analysis made it clear that the study hypotheses (H1-H5) are supported. Our first hypothesis suggested that data acquisition would positively relate to marketing analytics. As we suggested, data acquisition was related to marketing analytics ($\beta = 0.43$, $p < 0.001$). Tool acquisition was found to have a positive effect on marketing analytics ($\beta = 0.46$, $p < 0.001$). This validated H1 and H2. Regarding the association among marketing analytics and customer agility, our analysis supported the significant effect of marketing analytics on customer agility $\beta = 0.33$, $p < 0.001$). Our study also revealed a significant positive association among customer agility and customer satisfaction ($\beta = 0.68$, $p < 0.001$). Following the recommendations by Hair et al. (2021), our study indicated that marketing analytics use has an indirect influence on consumer satisfaction through customer agility ($\beta = 0.187$, $p < 0.001$). The results demonstrated that consumer agility fully mediated the link among marketing analytics and consumer satisfaction (see Table 5).

5.3. Testing the moderating effects

A hierarchical moderation regression analysis was performed to test for the moderation effect in the structural model (Hayes, 2013) PROCESS macro. Results in Table 6 revealed a significant association between the use of marketing analytics and market turbulence ($\beta = 0.63$; $p < 0.001$) and customer agility and market turbulence ($\beta = 0.41$; $p < 0.001$). The interaction terms between these variables lead to a change in the variance explained (adj-$R2$ = 0.36; $p < 0.001$). Our results revealed a positive and significant value for the interaction terms. Thus, H5 was supported. The analysis also indicated that a data-driven culture moderated the association among marketing analytics use-customer agility ($\beta = 0.71$; $p < 0.001$) and that between customer agility-customer satisfaction ($\beta = 0.29$; $p < 0.001$), confirming H6.

To further understand the model's practical effect, we used Cohen's (1988) "effect size *f2*", which is a measure of the prevalence of a phenomenon in the sample population. "Small, medium, and large effect sizes" were suggested by Cohen (1988), with corresponding operational definitions of 0.02, 0.15, and 0.35. As a result, our model predicted that the use of marketing analytics (*f2* = 0.61) and customer satisfaction (*f2* = 0.44) have a large effect size, while customer agility (*f2* = 0.26) has a medium effect size.

Table 5
Mediation testing (SmartPLS).

Path	β	P values
ANL→AGT→SAT	0.184	0.001

Table 6
Model coefficients for the conditional process models.

Predictor	β	SE	t	CI
Market turbulence				
Constant	1.039	0.04	−0.39	−0.05, 0.06
Firm size	−0.08	0.16	−0.58	−0.01, 0.19
Firm age	0.04	0.18	−0.10	−0.27, 0.01
Business type	0.03	0.11	−0.47	−0.19, 0.04
Marketing analytics adoption (ANL)	1.49***	0.02	7.34	0.21, 1.67
Customer agility (AGT)	1.24***	0.05	5.29	0.18, 1.35
Market turbulence (MAT)	0.69**	0.02	3.21	0.14, 1.29
ANL X MAT	0.65**	0.01	3.07	0.11, 1.04
AGT X MAT	0.38**	0.06	2.18	0.10, 0.82
Marketing analytics-driven culture				
Constant	1.346	0.17	−0.45	−0.08, 0.04
Firm size	−0.06	0.10	−0.19	−0.03, 0.09
Firm age	0.05	0.19	−0.34	−0.07, 0.06
Business type	0.02	0.10	−0.17	−0.11, 0.08
Marketing analytics adoption (ANL)	1.12***	0.04	5.02	0.36, 1.89
Customer agility (AGT)	0.44**	0.01	4.19	0.21, 1.57
Marketing analytics-driven culture (ANC)	0.19*	0.06	3.28	0.19, 1.36
ANL X ANX	0.67**	0.04	3.07	0.14, 1.21
AGT X ANC	0.21*	0.09	1.78	0.02, 0.72

Note: n = 4428, CI = 95% confidence interval. Unstandardized regression coefficients were reported. Bootstrap samples = 5000. One tail *t*-test was used for interaction terms. *** $p < 0.001$. ** $p < 0.01$. * $p < 0.05$.

6. Study 2: methodology

In study 2, we wanted to better establish a causal link between our

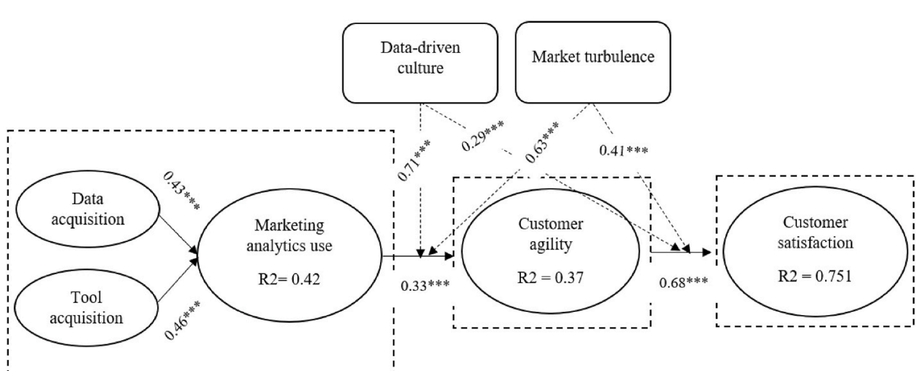

Fig. 2. Structural model results.

previously identified variables (e.g., marketing analytics use, customer agility, and customer satisfaction). According to Kline (2015), longitudinal data can help draw more accurate conclusions regarding the relationships between variables. As a result, we applied a Cross-Lagged Panel Model (CLPM) to data collected across three waves of our longitudinal investigation to confirm the results of study 1.

6.1. Sampling and measures

Due to the cross-sectional nature of the data in Study 1, we conducted an additional study using a longitudinal methodology to verify our hypotheses about the relationships between the constructs. To guarantee comparability between research, the same instrument items were utilised to assesses the constructs in both studies. In study 2, data were gathered in three separate waves from the same participants in study 1. These respondents were sent the same questionnaire three times, with six months between each. The three sets of data were matched since respondents were required for their names in the survey. There were 239 valid responses for our analysis.

We evaluated the scale properties using Cronbach's alpha, AVE, and composite reliability for "three separate measurement models", "one for each wave", were evaluated. Our analysis shows satisfactory results for all three waves. All items' loadings were above 0.7, demonstrating a high level of convergent validity. Following suggestions by Fornell and Larcker (1981), we evaluated the discriminant validity. The analysis revealed a satisfactory level of the discriminant validity of our study constructs.

6.2. Data analytics approach

In order to verify the validity of the suggested model in study 2, which used longitudinal data, we implemented CLPM. There are three benefits of CLPM that boost causal inference greatly. As stated by Cole and Maxwell (2003), one of the key components of CLPM is an autoregressive link among a construct and its previous state. Two-way effects between constructs can be ruled out by using CLPM, for another. It is common for constructs in business research (e.g., Xiao et al., 2019) to have mutual influences on one another, resulting in what is known as a "reciprocal effect". Because regression technique uses a variance-covariance matrix, distinguishing the direction of effect is not always easy. It is possible to determine the direction of causation among two constructs with high confidence once we have eliminated all possible reverse causality. Third, a time lag is used to evaluate the association between two constructs, so X comes before Y, as required by the temporal precedence requirement.

To analyse the connection between our study constructs, we used CLPM in accordance with the method described by Selig and Preacher (2009). The study factors (e.g., use of marketing analytics, customer agility, and customer satisfaction) were assessed three times for the CLPM-based casual process test.

6.3. Study 2: results

The results of a CLPM analysis revealed that the autoregressive paths of use of marketing analytics, customer agility, and customer satisfaction were significant. A significant correlation ($\beta = 0.62$, $p < 0.01$) was found between the use of marketing analytics at Time 1 and Time 2, and a positive correlation ($\beta = 0.57$, $p < 0.01$) was found between the use of marketing analytics at Time 2 and Time 3. Customer agility at time 1 was positively related to customer agility at time 2 ($\beta = 0.34$, $p < 0.01$), while customer agility at time 2 was positively related to customer agility at time 3 ($\beta = 0.49$, $p < 0.01$). Furthermore, there was a positive relationship between customer satisfaction at times 1 and 2 ($\beta = 0.51$, $p < 0.01$), and a positive association among consumer satisfaction at times 2 and 3 ($\beta = 0.32$, $p < 0.01$). All significant autoregressive paths were found, indicating that the current values of all model constructs were determined by their previous state. As a result, we needed to account for autoregression to conduct a causality test.

Regarding causal effects, our analysis revealed that use of marketing analytics at time 1 was found to have a significant influence on agility at time 2 ($\beta = 0.37$, $p < 0.01$). Moreover, there was a positive relationship between customer agility at time 2 and satisfaction at time 3 ($\beta = 0.35$, $p < 0.01$). This result revealed that the effect of marketing analytics uses changes over time. Further evidence that the causal linkages between the study constructs are unidirectional rather than reciprocal is provided by the finding that three-quarters of the reciprocal effects were not significant. This lends credence to the hypothesis of a causing effect.

Due to the directional nature of the hypotheses tested and the fact that Study 2 was a positive replication of Study 1, one-tailed tests were utilised in the moderation analysis replication. The results showed that H5 was supported because market turbulence positively and significantly moderated the effect of marketing analytics use at time 1 on customer agility at time 2 $\beta = 0.20$, p 0.01) and the effect of marketing agility at time 2 on customer satisfaction at time 3 ($\beta = 0.29$, p 0.01). We also found that a data-driven culture significantly and positively moderated the effect of marketing analytics use at time 1 on customer agility at time 2 ($\beta = 0.14$, p 0.01), and that the same culture significantly and positively moderated the effect of marketing agility at time 2 on customer satisfaction at time 3 ($\beta = 0.19$, p 0.01). These results are consistent with H6.

7. Discussion and implications

7.1. Key findings

Utilising longitudinal data, this paper aimed to develop and test a conceptual framework of the drivers and outcomes of customer agility and an across various industries in the UK context. On the basis of the dynamic capabilities' theory and the literature review, we suggested that marketing analytics use is a key driver of customer agility, while customer satisfaction was identified as an outcome of customer agility. In study 1, we collected and analysed data from 468 managers in different industries. Our analysis revealed that the marketing analytics has a significant influence on consumer agility. The analysis demonstrated that customer agility has a significant positive influence on customer satisfaction. These relationships were stronger in highly turbulent markets.

The analysis indicates that the acquisition of data and tools has a significant influence on the marketing analytics. This explains why the validation results for H1 and H2 are positive. These findings are corroborated in other studies (Akter et al., 2022; Ashrafi et al., 2019; Hajli et al., 2020). For instance, Tarn and Wang (2023) analysed how business analytics may help to enhance a company's decision-making process, while the implications of big data and predictive analytics on supply chain management and organisational performance were studied by Dubey et al. (2018). The use of business analytics in IT was recently underlined in research by Kalaignanam et al. (2021). We received valuable insights from our studies. We have taken ideas from these studies and used them to construct a model that shows how the acquisition of data and tools may enhance marketing analytics. What this means is that if a company collects useable data and chooses proper analytics technologies, it will be able to effectively deploy marketing analytics. The findings indicate that there is a relationship between customer agility and customer satisfaction. The notion in question has also garnered support from Gligor and Bozkurt (2021), who have demonstrated the influence of agility on consumer involvement. This stimulated our interest in exploring the potential of marketing analytics in enhancing customer agility, hence influencing customer satisfaction. This finding has garnered support from previous research conducted by Sun et al. (2017) and Chatterjee et al. (2021). Previous research has indicated that the utilisation of marketing analytics tools in various organisational contexts has a significant positive effect on process performance (e.g., Auh et al., 2022; Hossain et al., 2022). Additionally, the presence of marketing analytics capabilities has been found to exert a substantial influence on the business decision-making process within organisations, which is considered crucial for their operational activities (Liang et al., 2022a,b). Drawing upon the findings of this study, our model has been constructed to elucidate the manner in which marketing analytics, influenced by the acquisition of data and tools, might enhance customer satisfaction by bolstering customer agility.

This result has received support from earlier studies (e.g., Sharma et al., 2014; Sun et al., 2017). The existing studies have supplemented that use of marketing analytics tools in any type of organisation has effective impact on the process performance of the organisation and also marketing analytics capabilities have effective impact to influence the business decision of the organisations, which are considered vital for business activities of the organisations. Borrowing concepts from these studies, we have been able to develop our model that highlights how marketing analytics, impacted by data acquisition and tool acquisition, would improve customer satisfaction through improving customer agility.

In study 2, longitudinal data were utilised to emphasise causal direction in on the link between marketing analytics use, customer agility, and customer satisfaction by employing CLPM. The results revealed that marketing analytics use at time point T1 has a significant and positive influence on customer agility at time point T2, while customer agility at time point T2 was related to customer satisfaction at time point T3. These findings indicate strong temporal effects between marketing analytics use, customer agility, and customer satisfaction. This study results expand previous research by exploring the links between marketing analytics use, customer agility, and customer satisfaction and emphasising causal relationships with longitudinal data, which enable us to understand the mechanism on how marketing analytics can boost customer satisfaction via customer agility.

While many businesses have improved their IT skills to become more agile, the benefits of company IT capabilities on agility have been the subject of conflicting empirical research (Ashrafi et al., 2019). In this regard, several studies demonstrate that not all businesses who put resources into data analytics (a crucial company IT capacity) see consequent improvements in their agility (Mandal, 2018). Analysis revealed that marketing analytics use is a key driver of customer agility, which in return improves customer satisfaction. This result augments the previous literature on the marketing analytics-customer agility-and customer satisfaction relationships, which are stronger in high market turbulence. These results are consistent with previous studies demonstrating that marketing analytics is a key driver of customer agility and satisfaction (i.e., Elazhary et al., 2022; Zhou et al., 2019).

7.2. Theoretical implications

In this research, we examined how a data-driven culture affects the uptake of marketing analytics tools. The dynamic capability view theory (Zahoor et al., 2022) and other related work (e.g., in Gyemang and Emeagwali, 2020) served as a theoretical lens for this study. This enabled us to build on prior research to provide a novel and substantial theoretical model which could efficiently allocate company assets to satisfy customers via customer agility. This is a significant advance in the theory. Our study's significance lies not in its breadth of coverage but rather in its location at the junction of areas that rapidly shifting economic conditions force nearer and nearer to each other. In this way, the research contributes to the stream of the dynamic resource-based view and at the same time enhances our understanding of customer agility and customer satisfaction by a thorough examination of their interrelationships within the context of a data-driven culture. Moreover, our study indicated that marketing analytics use, and customer agility appeared to influence customer satisfaction positively over time, demonstrating the temporal effects between these variables.

Using consumer agility as a mediator, the research suggests that marketing analytics is related to customer satisfaction. This novel proposal has the potential to strengthen the model by increasing its explanatory power. We believe this to be one of the study's most important theoretical contributions. Customer agility is a mediator; hence, verifying its indirect impacts might make the model more robust (Jafari-Sadeghi et al., 2022). Adopting a marketing analytics solution is the focus of this research within the larger framework of a data-driven organisational culture. For this reason, any generic use model could have been used; nevertheless, better outcomes might have been secured by taking into account certain more appropriate parameters. However, no such model was used. This adds another theoretical layer to the work.

This research challenges the widely held belief that boosting product quality and trust alone would lead to satisfied customers, by demonstrating to the corporate world that boosting customer agility within the framework of a data-driven cultural climate and using marketing analytics tools may also lead to increased customer satisfaction. In the rapidly evolving digital economy, a culture of data-driven innovation is essential to maintaining customer satisfaction. This is also presented as a theoretical advance made possible by this investigation. This research extends the marketing analytics literature by exploring its effect on customer agility. To the best of our knowledge, our examination is first to investigate this relationship using longitudinal data.

While both customer agility (Hajli et al., 2020) and marketing analytics are seen as essential, the "Marketing Science Institute" (MSI) has designated customer agility as a top research area to focus on (Zhou et al., 2018). This examination shows that customer agility is a superior talent that helps businesses to be more successful in their chosen field of marketing. This discovery contributes to the current literature on customer agility by highlighting three analytics drivers as dynamic capabilities to improve the use of marketing analytics (e.g., Ashrafi et al., 2019; Kalaignanam et al., 2021). Therefore, our examination expands the previous studies on marketing analytics, customer agility, and customer satisfaction in a market turbulence environment.

Finally, our research provides an in-depth comprehension of how market volatility affects the connection between marketing analytics, customer agility, and customer satisfaction. By adopting the dynamic capacities perspective, we provide light on the moderating effect of market volatility on these connections. According to the results, the impact of marketing analytics on customer agility is greatest in times of extreme market volatility.

7.3. Practical implications

Practitioners and managers of marketing analytics can find useful insights in this research for enhancing customer satisfaction. This research emphasises the need for leaders who are fostering a data-driven culture to consider workers' perspectives in the workplace. For marketing analytics to have a greater effect and for businesses to be more agile in responding to their customers' needs, a data-driven culture is essential.

Despite the hesitancy of certain organisations to invest in marketing analytics due to their perceived inability to showcase its value, our study provides empirical evidence that marketing analytics does indeed yield positive outcomes. The findings of our study demonstrate that the implementation of environmental scanning practises enables enterprises to effectively monitor and analyse their external environment in a timely manner. This, in turn, enhances their ability to respond promptly to consumer needs and preferences, ultimately leading to higher levels of customer satisfaction. Specifically, it has been observed that the utilisation of marketing analytics tends to result in more favourable outcomes for companies that operate within a highly volatile market environment. Therefore, it is advisable for companies aiming to maintain flexibility in highly competitive markets to utilise marketing analytics as a means of guiding their strategy in order to effectively adapt to shifts in client preferences and the competitive environment. Furthermore, it is worth noting that prior research has acknowledged the potential business value associated with analytical activities. However, our study aims to contribute additional insights by examining the assessment of the potential business impact of marketing analytics specifically from the standpoint of dynamic capabilities. This study suggests that there is a need for greater diversity in analysing the business impact of marketing analytics. It highlights that marketing analytics may result in intermediary results, such as customer agility, rather than directly influencing customer satisfaction.

Managers may derive several insights and considerations from this research. Our study revealed that putting marketing analytics tools in the workplace would not immediately inspire unique ideas to increase customer agility and customer satisfaction in the context of data-driven culture elements. It is imperative for marketing analytics professionals operating in the technical domain to effectively communicate their findings and acknowledge the constraints of their study to the relevant employees. It is imperative for the organisation to provide comprehensive training to all employees regarding the utilisation of marketing analytics. Organisations have the potential to offer "self-service" marketing analytics solutions to facilitate the acquisition of data analysis skills by their employees. Additionally, organisations should actively promote and acknowledge the valuable contributions made by their employees in this domain. Additional efforts should be undertaken to enhance the organisation's data scanning capability in order to effectively extract the most valuable data from various pertinent sources. The concept has been augmented by the theoretical framework of dynamic capabilities. Our research shows that a company's ability to quickly adapt to changing consumer preferences has a significant impact on the success of its use of analytics in marketing. Effective marketing analytics are evident in consumer segmentation and targeting programmes, individualised product and service delivery, original content creation, and marketing metrics. Hence, marketing analytics capabilities must be developed and used correctly to detect, grasp, and transform opportunities via customer agility.

On the basis of our findings, we recommend that managers prioritise customer agility alignment. Although our findings from the matching and mediation perspectives are compelling, we argue that companies should also put resources into developing their conversion processes, which are what provide the genuine dynamic capacity shown in customer agility. In addition to gathering and analysing data on product-market gaps, highly responsive businesses may take advantage of this arbitrage by rearranging and repurposing their resources. But a coordinating mechanism capable of assimilating sensory input and structuring the reaction is required for this to be accomplished successfully. Ad hoc committees or bidextrous structures that can handle the day-to-day grind but also have the flexibility to take on new, unexpected tasks to improve customer agility are two examples. This study's findings should serve as a wake-up call to managers who want to boost customer satisfaction by bringing out the importance of marketing analytics investments and customer agility.

8. Limitations and directions for future studies

Our study has some limitations, but these could be used to offer new insights and directions for further examinations. First, our study developed and test a conceptual framework using data from various industries. Future research could apply and test our proposed model in specific industry such as retail or IT sectors. It is critical to understand in each industry how marketing analytics are developed, as well as through what mechanisms they develop customer agility and customer satisfaction, and how that can be captured. Second, our study has been conducted in a single country (i.e., UK). Future studies could test our proposed model in different countries to examine the effect of national culture on the relationship between our study variables. Cross-cultural examinations are also required to improve the generalizability of our findings and offer a holistic perspective in various environments. Third, our study used marketing analytics as a key driver of customer agility. Previous research revealed that big data analytics is a key driver of customer agility (e.g., Zhou et al., 2018). Future examinations could test other factors such as big data analytics and information infrastructure. Fourth, we used customer satisfaction as an outcome of our study. Future research could use other variables as an outcome of customer agility, such as firm performance and firm value. Moreover, we used primary data to measure the study variables. We suggest that future examinations could use secondary data to measure customer agility and customer satisfaction. Finally, our examination used market turbulence as a moderator in the link between marketing analytics use, customer agility, and customer satisfaction. Future studies could use customer loyalty and firm creativity as a moderator on these relationships.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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(None)

Appendix A

Please use the following scale to describe your opinion towards the following questions: 5 = Strongly Agree (SA), 4 = Agree (A), 3 = Neutral (N), 2 = Disagree (D) and 1 = Strongly Disagree (SD).

Items	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Customer satisfaction					
"Increasing customer satisfaction".	(Mithas et al., 2011; Raguseo and Vitari, 2018)				
"Delivering more value to our customers".					
"Improving the delivery of what our customers want".					
"Retaining valued customers to a greater extent".					
Customer agility					
"We continuously try to discover additional needs of our customers of which they are unaware".	(Narver et al., 2004; Shirazi et al., 2022; Slater and Narver, 2000).				
"We extrapolate key trends to gain insight into what users in a current market will need in the future".					
"We continuously try to anticipate our customers' needs even before they are aware of them".					

(*continued on next page*)

(*continued*)

Items	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
"We attempt to develop new ways of looking at customers and their needs".					
"We sense our customers' needs even before they are aware of them".					
"We respond rapidly if something important happens with regard to our customers".					
"We quickly implement our planned activities with regard to customers".					
"We quickly react to fundamental changes with regard to our customers".					
"We are fast to respond to changes in our customers' product or service needs".					
Marketing analytics use					
"I believe that marketing analytics solution can help the organisation for taking accurate decision at appropriate time".	(Akter et al., 2019; Sharda et al., 2016).				
"Adoption of marketing analytics solution can help to predict appropriate actions to be taken for betterment of the organisation 2.					
"Full adoption of marketing analytics solution is important to realize all the advantages that it can provide".					
"Effective readiness plan is important for adoption of marketing analytics solution".					
"Adoption of marketing analytics solution is a part of organisation's data-driven culture".					
Data acquisition					
"I understand the importance of acquiring appropriate data for marketing analytics solution".	(Cosic et al., 2015; Gnizy, 2019; Gunasekaran et al., 2017; Sharma et al., 2014).				
"Appropriate planning is essential to acquire different kinds of data from different sources".					
"Acquiring both the external and internal data of the organisation is essential for effective marketing analytics solution".					
"It is difficult to acquire appropriate data for effective marketing analytics solution".					
Tool Acquisition					
"Appropriate tool acquisition is essential for effective marketing analytics solution".	(Bayrak, 2015; Sun et al., 2017).				
"Tool acquisition is expensive".					
"Tool training is important for the employees who will use the system".					
Market turbulence					
"In our kind of business, customers' product preferences change quite a bit over time".	(Elazhary et al., 2022; Jaworski and Kohli, 1993).				
"Our customers tend to look for new product all the time".					
"We are witnessing demand for our products and services from customers who never bought them before".					
"New customers tend to have product-related needs that are different from those of our existing customers".					
Data-driven culture					
"We consider data a tangible asset".	Yu et al. (2021).				
"We continuously assess and improve the business rules in response to insights extracted from data".					
"We continuously coach our employees to make decisions based on data outcomes".					

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